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Assessing the utility of topographic variables in predicting structural complexity of tree stands in a reforested urban landscape

K. Sithole, J.O. Odindi*, O. Mutanga

School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa

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ABSTRACT

The transformation of natural landscapes into impervious built-up surfaces through urbanization is known to significantly interfere with the ecological integrity of urban landscapes and accelerate climate change and associated impacts. Although urban reforestation is widely recognised as an ideal mitigation practice against these impacts, it often has to compete with other lucrative land uses within an urban area. The often limited urban space provided for reforestation therefore necessitates the optimization of the ecological benefits, which demands spatially explicit information. The recent proliferation of tree stands structural complexity (SSC) and topographic data offer great potential for determining the ecological performance of reforested areas across an urban landscape. This study explores the potential of using topographic datasets to predict SSC in a reforested urban landscape and ranks the value of these topographic variables in determining SSC. Tree structural data from a reforested urban area was collected and fed into a tree stand structural complexity index, which was used to indicate ecological performance. Topographic variables (Topographic Wetness Index, slope, Area Solar Radiation and elevation)- were derived from a Digital Elevation Model (DEM) and used to predict SSC using the Partial Least Squares (PLS) regression technique. Results show that SSC varied significantly between the topographic variables. Results also show that the topographic variables could be used to reliably predict SSC. As expected, the Topographic Wetness Index and slope were the most important topographic determinants of SSC while elevation was the least valuable. These results provide valuable spatially explicit information about the ecological performance of the reforested areas within an urban landscape. Specifically, the study demonstrates the value of topographic data as aids to urban reforestation planning.

1. Introduction

Urbanization, characterised by transformation of natural landscapes into impervious built-up surfaces, is regarded as a major driver of environmental change (Deosthali 2000; Jusuf et al., 2007). Such transformation is associated with, among others, natural landscape fragmentation and associated adverse effects (Hanski, 2005), air pollution (Xu et al., 2016), noise pollution (Singh and Davar, 2004), climate change (McDonald et al., 2008), biodiversity loss (Le-Xiang et al., 2006) and thermal stress (Tan et al., 2010). Consequently, urban reforestation (used in this study to mean re-establishment of green landscape by planting native tree species and natural vegetation re-generation in designated), is increasingly becoming a popular approach to dealing with adversities associated with urban natural landscape loss (Liski et al., 2000; Luyssaert et al., 2008, Oldfield et al., 2015; Silver et al., 2004). Reforestation, particularly by a range of indigenous tree species, mitigates for biodiversity loss by increasing habitat diversity, which accommodates a wider variety and abundance of plant and animal life (Benayas et al., 2009; Harrison et al., 2003; Le et al., 2012; UNFCCC, 2013). Furthermore, reforested areas act as effective carbon sinks, valuable for climate change mitigation (Liski et al., 2000; Luyssaert et al., 2008; Oldfield et al., 2015; Silver et al., 2004). Other benefits associated with urban reforestation include assimilation of air pollutants (Yin et al., 2011), recreation (Arnberger, 2006), flood attenuation (Hoang and Fenner, 2016) and water purification (Fiquepron et al., 2013). Unfortunately, urban reforestation is often in competition with "higher return for investment" activities such as real estate, industrial establishments, urban agriculture and other commercial establishments. This necessitates that reforestation benefits are maximised within the limited urban land by optimising their ecological performance. Such optimization requires spatially explicit information about the ecological performance of urban reforested areas.

Tree stand structural complexity (SSC) is known to be a reliable indicator of a forest's ecological performance, and has been used to determine among others a forest's carbon sequestration, habitat diversity and biodiversity change (Franklin and Van Pelt, 2004, Kane

* Corresponding author.
E-mail address: odindi@ukzn.ac.za (J.O. Odindi).

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et al., 2010; Lamonaca et al., 2008; Lindenmayer et al., 2000; McElhinny et al., 2005; McKenny et al., 2006; Neumann and Starlinger, 2001). Wang et al. (2011) for instance noted a positive relationship between aboveground carbon stocks and SSC in spruce-dominated forest stands in New Brunswickk, Canada, while Pastorella and Paletto (2013) established a positive relationship between SSC and habitat diversity in Trentino forests. Tanabe et al. (2001) established a relationship between SSC to local insect diversity, while McKenny et al. (2006) noted that SSC was useful for monitoring the effect of different silvicultural management practices on eastern red-backed salamander populations in hardwood forests. Garbarino et al. (2009) found that SSC is useful in determining the influence of anthropogenic factors on the health of European larch forests. Based on the above examples, we hypothesize that determination of SSC would be a useful indicator of the ecological performance of a reforestation initiative within an urban landscape.

To date, studies have relied on single stand attributes to determine tree stand ecological performance. These include leaf area index (Arx et al., 2013; Davis et al., 2000; Moser et al., 2007), stem diameter (Chave et al., 2005; Zheng et al., 2008), net primary productivity (Aragão et al., 2009; Girardin et al., 2010), tree height (Seavy et al., 2009), basal area (Liang et al., 2007; Waltz et al., 2003) and species composition (Ruiz-Labourdette et al., 2012; Valencia et al., 2004). Other studies have combined multiple attributes to determine tree stand ecological performance. These include the Structural Complexity Index using ground vegetation, shrub, log and litter attributes (Barnett et al., 1978) and the Stand Diversity Index using variations in species richness, tree spacing, diameter at breast height (DBH) and crown size (Neumann and Starlinger, 2001). Others include the Structure Index based on covariance in height and DBH (Staudhammer and LeMay, 2001) and the Structural Complexity Index (Holdridge, 1967) based on canopy height, stem diameter, basal area and species richness. The adoption of multiple SSC attributes is particularly appealing as it offers a multi-dimensional index that include species (i.e. species richness), horizontal (i.e. basal area) and vertical (i.e. canopy height) characteristics, which is more robust in determining the value of a reforested area. Hence, Structural Complexity Index by Holdridge (1967) has for a long time been popular due to its commonality with existing data inputs within forestry inventories and processing simplicity. Generally, existing approaches that seek to determine tree stand structural complexity and ecological performance have mainly used ecological parameters.

A range of factors could be used to determine the distribution of SSC in remnant urban vegetation fragments or reforested areas. These include surface physical characteristics, settlement density and management decisions (Sanders, 1984). Generally, the value of these factors in determining SSC vary. Specifically, surface physical characteristics like variation in topography offer great potential for predicting SSC. As aforementioned, a number of studies in among others Toronto (Ramsey-Brown, 2015), Sheffield (Davies et al., 2008) and Cincinnati (Berland et al., 2015) have identified topography as major factor in urban vegetation abundance and motivation for conservation of urban woodlands. Whereas initial adoption of topographic variables in determining ecological characteristics was impeded by lack of good quality topographic data, recent technological advancements that have led to a proliferation of good quality Digital Elevation Models (DEMs) (Vaze et al., 2010) offer great potential in determining urban forest's ecological value. Specifically, DEMs offer large-area data coverage, hence suitable for comparing varied reforestation regimes, while recent improvements in their spatial resolutions allow for determination of finer structural variations. Furthermore, the growth in freely available high-resolution DEM data makes them ideal for cost-effective operational use.

Previously, surface topographic characteristics have been used to model other tree attributes like tree diameter (Aiba et al., 2004), canopy structure (Aiba et al., 2004; Webb et al., 1999), tree community composition (Baldeck et al., 2013; Homeier et al., 2010; Zhao et al., 2015), and tree species (Kuebler et al., 2016; Lan et al., 2011). However, there is paucity in literature on the use of topographic characteristics to predict SSC. In this study, we hypothesize that topographically related environmental gradients that influence vegetation growth as well as stand ages may influence SSC. The topographic Wetness Index (TWI) for instance is a steady state hydrological model, which represents the relative distribution of soil surface moisture based on the terrain surface. Due to the effect of gravity, TWI has shown a positive correlation with surface soil moisture (Wilcke et al., 2011), soil fertility (Ou et al., 2014; Wilcke et al., 2008, Wolf et al., 2011), soil nutrient pooling (Oliveira-Filho et al., 2001, Tanner et al., 1998, Wilcke et al., 2011) as well as soil's microbial activity (Lan et al., 2011). Slope steepness determines soil erosion and deposition (Vorpahl et al., 2012; Webb et al., 1999). Steeper slopes for instance are often characterised by thinner soil depths, impeding tree growth (Ließ et al., 2011; Oliveira-Filho et al., 2001; Wolf et al., 2011), while gentle slopes and flat surfaces are commonly characterised by moisture, soil, nutrients and litter convergence, hence nutrient pooling. An area's solar radiation (ASR) is the variation in solar exposure due to slope face direction. Therefore ASR is strongly related to insolation and air temperature (Fries et al., 2009), precipitation (Rollenbeck, 2006) and transpiration (Kuebler et al., 2016; Wang et al., 2009). Elevation has been found to influence soil fertility (Ou et al., 2014; Wilcke et al., 2008; Wolf et al., 2011), soil moisture (Wilcke et al., 2011), soil nutrient pooling (Oliveira-Filho et al., 2001; Tanner et al., 1998; Wilcke et al., 2011) and surface air temperature (Fries et al., 2009). Generally, topographic heterogeneity creates micro-habitat gradients that influence tree growth and hence SSC. Hence, using SSC derived from local ecological stand structural attributes (canopy height, tree diameter, stem density and species richness), this study sought to: i) predict the spatial patterns in SSC within a reforested urban landscape using stand age and topographic variables (TWI, slope, ASR and elevation) and ii) rank the value of the above named variables in determining SSC.

2. Materials and methods

2.1. Study area and sampling

The study area is located within the recently created Buffelsdraai landfill site north of South Africa's port city of Durban, South Africa (Fig. 1). The reforestation programme was initiated as a buffer zone around the landfill site to offset carbon emissions associated with South Africa's 2010 FIFA World Cup hosted by the city, to mitigate biodiversity loss and to improve local livelihoods by providing employment opportunities. The buffer zone is 800 ha, with the 117 ha active landfill located at the centre. The buffer zone is mainly surrounded by urban settlements, grazing land and sugar cane farms, a major economic activity in the area. The study area is characterised by humid subtropical climate influenced by the warm Indian Ocean currents. Winter months (May to September) are warm and dry, with average maximum temperatures of 22 °C while summer months (November to March) are hot and humid with average maximum temperatures at 27 °C. Total mean annual precipitation is approximately 1000 mm. The area is underlain by the Dwyka Tillite – a glacial conglomerate parent material that is base-rich, hard and resistant to weathering, hence its un-even topography. Glenrosa soil dominates the upper- to mid- slopes while the gentle to flat areas are dominated by the Oakleaf soils, due to deposition (McCulloch, 2014).

Reforestation in the study area was initiated in 2009/2010 and seedlings are planted in new areas annually (2009/2010, 2010/2011, 2011/2012, 2012/2013, 2013/2014 and 2014/2015) within the buffer zone (Fig. 2b). As at January 2015, 660 523 indigenous trees had been planted in 412 ha of land. Common tree species are the Common hookthorn (*Acacia caffra)*, Pale-bark sweet thorn (*Acacia natalitia)*, Coastal golden-leaf *(Bridellia micranta)*, Climbing flat bean *(Dalbergia obovate)*,

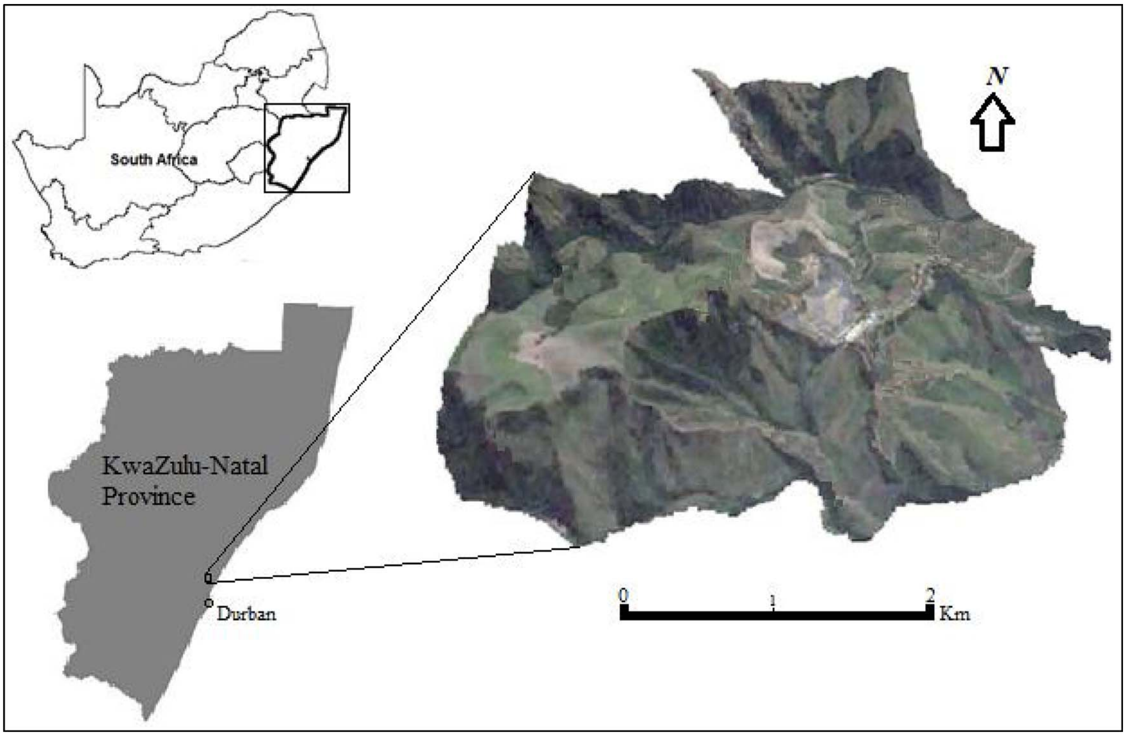

Fig. 1. The study area.
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African coral tree *(Erythrina caffra)*, Sausage tree *(Kigelia Africana)*, Umzimbeet *(Millettia grandis)* and Water berry *(Syzygium cordatum)*. After establishment, the stands are not actively maintained, except removal of invasive species, to allow for maximal regeneration of species. Whereas a range of species are used for the reforestation project, they are not stratified, they are evenly planted within stands to maximize ecological heterogeneity. The rest of the buffer zone, previously dominated commercial sugarcane plantation, is now covered by grass (utilized for livestock grazing), scarp forest and pockets of weeds.

Ninety sampling plots were selected for the study using stratified random sampling (Fig. 2a). The sampling plots were deemed an adequate representation of the major topographic variations within the study. Whereas tree seedlings have been planted in new areas annually since 2009 (Fig. 2b), only reforested zones that were at least two years old (i.e. planted in 2009/2010, 2010/2011 and 2011/2012) were sampled as they were deemed to have attained sufficient growth and cover. Using coordinates of the sampling plots' central points as reference, sampling plots measuring 30 × 30 m and at least 60 m apart (to avoid overlap in topographic coverage) were selected.

2.2. Data for stand structural complexity

To determine SSC, stand structural attributes (canopy height, tree diameter, stem density and species richness) were measured at each sampling plot. A levelling rod was used to measure canopy height with ~0.05 m accuracy (canopy height in this study refers to the height of the highest branch of the tree), and the mean canopy height of the sampling plots determined. In this study, mean tree diameter-at-ankle-

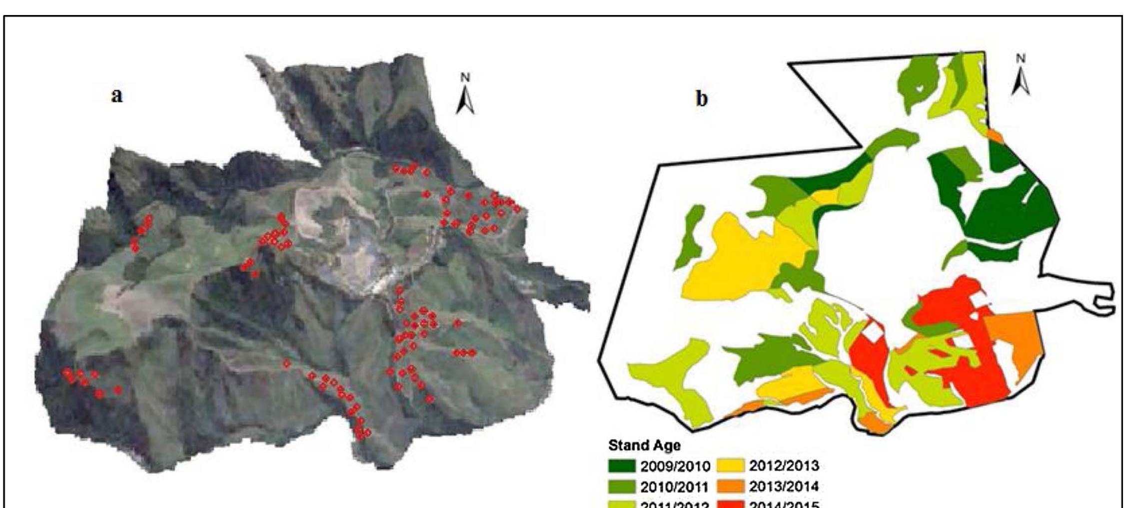

Fig. 2. Sampling points and stand ages.
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Table 1
Classes of topographic variable ranges.

Topographic variable	Class Name	Class Range
TWI	Ridges	< 10
	Intermediate	10–15
	Depressions	> 15
Slope	Fairly Flat	< 10°
	Intermediate	10–15°
	Steep	> 15
ASR	Low	< 585 999
	Intermediate	586 000–632 999
	High	> 633 000
Elevation	Low Altitude	< 190 m
	Intermediate	190–230 m
	High Altitude	> 230 m

height (DAH), instead of mean diameter-at-breast height (DBH) was used to determine tree diameter of the sampling plots as recommended in literature (Maltamo et al., 2009; Pommerening, 2002; Van Leeuwen and Nieuwenhuis, 2010; Wolter et al., 2009). Paradzayi et al. (2008) and Way et al. (2006) note that DBH measurement, as a determinant of tree diameter at ~1.3 m height is not suitable in an area with tree canopy height of approximately 1.3 m. Furthermore, multiple studies (Paradzayi et al., 2008; Tietema, 1993; Van Sambeek and McBride, 1991; Way et al., 2006) have found DAH to be as useful as DBH in determining tree diameter. To determine stem density, the total number of trees per plot was divided by the plot area. Species richness was established by counting the number of species within each plot.

The four aforementioned ecological stand attribute data were used to determine structural complexity index (HC) using simple linear combination of common stand structural parameters (Eq. (3.1)) as originally proposed by Holdridge (1967). The approach's incorporation of species diversity and horizontal and vertical stand dimensions in determining SSC makes it an attractive indicator of other forest attributes such as habitat diversity, biodiversity, ecological restoration and carbon sequestration (Franklin and Van Pelt, 2004; Kane et al., 2010; Lamonaca et al., 2008; Lindenmayer et al., 2000; McElhinny et al., 2005; McKenny et al., 2006; Neumann and Starlinger, 2001). Tree diameter and stem density informs the index's horizontal dimension, while canopy height informs the index's vertical dimension and as adapted from Holdridge (1967) is expressed;

$$HC = H \times DAH \times n \times N \tag{3.1}$$

Where HC is the Structural Complexity Index, H is the canopy height, DAH the diameter at ankle height, n the number of stems per ha, and N is the number of species.

2.3. Topographic data

All topographic variables (i.e. TWI, slope, ASR and elevation) were derived from a high resolution (2 m) contour map of the area using ArcGIS 10.3. The contour map was first converted into a Digital Elevation Model (DEM), with a Pearson correlation of 0.99 using ground elevation measurements from a Trimble Geo 7X GPS unit. The DEM was then used to derive all the above named topographic variables. Particularly, the TWI provides a quantitative representation of the spatial variation in soil moisture based on the terrain unevenness (Sörensen et al., 2006). Within a GIS environment, the TWI is determined for each pixel by combining local upslope contribution area (i.e. cumulative higher elevation pixels) (Hojati and Mokarram, 2016). The current study used Eq. (3.2) as adopted from Schmidt and Persson (2003). In ArcGIS, the border pixels have zero flow accumulation (FA) value, hence the need to add 0.001 to FA. Also ArcGIS generates slope percentage (S) in degrees, hence its division by a factor of 100 to convert to radians. Furthermore, if the S is zero (i.e. flat slope) the tan of it would be zero, which would generate undefined pixel values, hence the addition of 0.001 to S.

$$TWI = \ln (FA + 0.001)/((S/100) + 0.001) \tag{3.2}$$

Where TWI is the topographic wetness index, FA is the flow accumulation, and S is the slope percentage.

In this study, threshold for the topographic variables, i.e. TWI, slope, ASR were determined based on recommendation by Moore et al. (1991), Murphy et al. (2010) and Roberts and Cooper (1989), respectively. Due to the commonly localised nature of altitudinal variability, elevation threshold was determined based on the study area's difference between the highest and lowest points.

2.4. Statistical analysis

To determine differences in SSC within each topographic variable, class ranges were delineated as shown in Table 1 and spatial depictions generated. Using IBM SPSS Statistics 24, a One Way ANOVA was then conducted to determine whether there were significant differences in SSC between the respective topographic ranks. Where post-hoc testing was necessary, Tukey's tests were conducted to evaluate pairwise differences among the topographic ranks.

2.5. Predictive model

The adoption of Partial Least Squares (PLS) technique in ecological studies has recently grown significantly (Carrascal et al., 2009; Luedeling and Gassner, 2012; Peerbhay et al., 2013; Ramoelo et al., 2013; Serbin et al., 2015). The PLS technique is one of the new modelling approaches within the family of Structural Equation Modelling (SEM) techniques. These SEM techniques overcome the common limitations of first family modelling techniques such as assumption of simple model structures, requirement for all variables to be observable and assumption that all variables are measured without error (Haenlein and Kaplan, 2004). The SEM techniques allow for the construction of latent variables as a function of the predictor variables. They also allow for explicit modelling error of measurement for the predictor variables (Haenlein and Kaplan, 2004). The PLS technique compresses explanatory information derived from the predictor variables (i.e. topographic variables) into a few non-correlated latent components that have maximum covariance with the response variable (i.e. SSC) (Carrascal et al., 2009; Maestre, 2004). The PLS regression is computed through linear combinations of the latent components and their weighted explanatory power on the response variables, and can be statistically expressed by Eqs. (3.3) and (3.4). The PLS technique is particularly appealing for its ability to minimise non-explanatory noise, identify relevant predictor variables and is applicable in studies with small sample sizes (Chin and Newsted, 1999; Haenlein and Kaplan, 2004).

$$X = TP' + E \tag{3.3}$$

$$Y = UQ' + F \tag{3.4}$$

where X represents the matrix of the predictor variables (topographic variables), Y is a matrix of the response variable (SSC), T is a factor score matrix, U is the scores for Y, Q is the Y loadings, P is the X loadings, E is the residual for X or a noise term, and F is the residuals for Y (Mehmood et al., 2012; Peerbhay et al., 2013).

In this study PLS was used to predict SSC using topographic variables within the MATLAB statistical environment (PLS Toolbox).

2.6. Model pre-treatment

The PLS technique is informed by the variance in the response variable as a function of the predictor variables. Without pre-treatment, the actual data sample values of the predictor variables would influence the PLS regression differently, based on sample size instead of variance

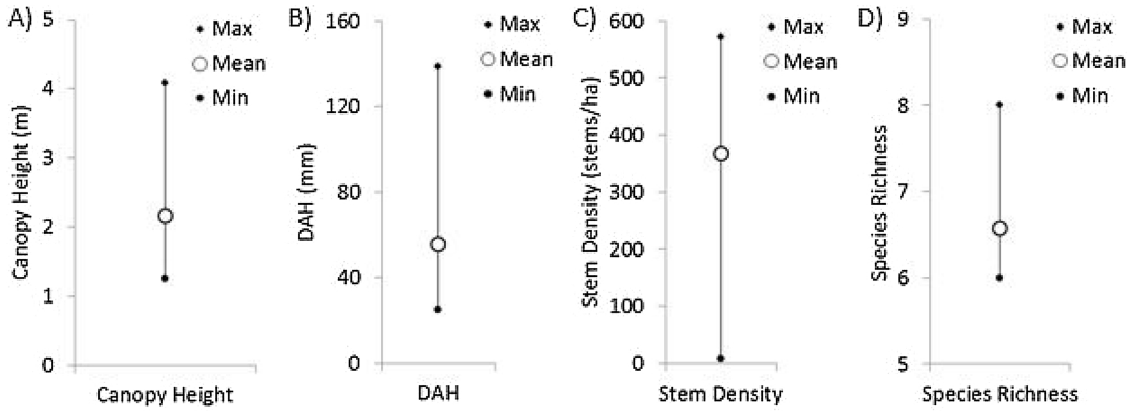

Fig. 3. Mean, maximum and minimum values of A) canopy height, B) DAH, C) Stem density and D) species richness across the re-forested area.
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(van den Berg et al., 2006). The current study used the auto-scale pretreatment method, making topographic data samples of all sizes equally important in predicting SSC. Auto-scaling first scales all variables to unit variance by dividing them by their standard deviations according to Eq. (3.5), and then centres them by subtracting their means according to Eq. (3.6), hence ensuring that all variables are equally important regardless of their units and value size.

$$\tilde{x} = \frac{x - \bar{x}}{s} \tag{3.5}$$

$$\hat{x} = \tilde{x} - \bar{x} \tag{3.6}$$

where x represents the value of the variables, $\tilde{x}$ is variables' values after scaling, $\hat{x}$ is variables' values after mean centring, $\bar{x}$ is the means of the variables, and s is the standard deviations of the variables (van den Berg et al., 2006).

2.7. Model optimisation

Selection of the optimal number of latent variables is a critical step in the optimisation of the PLS model (Mehmood et al., 2012). Due its simplicity and reliability for optimising the PLS model through latent component selection, Cross-Validation (CV) has become a common PLS process. Cross-Validation (CV) is computed by iteratively dividing the data into a number of subgroups with one of the subgroups reserved for validation. At each data division, their respective PLS models is generated from sub grouped data over a multiple number of latent components. After developing each model, differences between actual and predicted response variables are computed for validation data at each number of latent components. The sum of squares of the differences in actual and predicted response variables computed at each number of latent variables is used to compute the predictive residual sum of squares (PRESS), which estimates the predictive ability of the model at each latent variable number. During this iterative process, the number of latent components is systematically increased until the PRESS shows that increased latent components does not improve model predictive power. Hence, latent variables that retain high level of noise and multicollinearity among variables are removed from the PLS model (Mehmood et al., 2012; Peerbhay et al., 2013; Tobias 1995). There are multiple cross validation methods available, which divide these subgroups differently. The current study used the venetian blinds cross validation method as the data was relatively large with randomly ordered samples. The latent components selected through this optimization process were used to develop the final model to predict the SSC. The PLS models were derived and used to generate SSC spatial maps.

2.8. Assessment of prediction accuracy

To evaluate the predictive power of a PLS model, the Root Mean Square Error of Cross Validation (RMSECV), a final process in the PLS model was used. To determine the relative importance of the topographic and stand age variables in predicting the SSC in the reforested areas, the PLS process offers the computation of Variable Importance in Projection (VIP). The VIP computes scores which are informed by the importance of each predictor variable (i.e. topographic variables) in explaining the response variable (i.e. 5) (Wold et al., 2001). These are ranked scores as defined by Eq. (3.9). It is on the basis of the VIP scores that the importance of the topographic variables on the SSC was ranked.

$$\mathrm{VIP_k} \sqrt{K \sum_{a=1}^{A} \left[(q_a^2 t_a^T t_a)(w_{ak}/||w_k||^2)\right] / \sum_{a=1}^{A} (q_a^2 t_a^T t_a)} \tag{3.9}$$

Where $\mathrm{VIP_k}$ is the importance of the kth topographic variable based on a PLS model with a latent variables, K is the total number of topographic variable, w_{ak} is the corresponding loading weight of the kth topographic variable in the *ath* latent variable, and q_a, t_a and w_a are the column vectors.

3. Results

Fig. 3 shows the mean, maximum and minimum values of tree stand structural complexity index ecological inputs (i.e. canopy height, DAH, Stem density and species richness) across the reforested area. Whilst Fig. 4 shows the spatial distribution of the topographic variables (TWI – a, slope-b, Area Solar Radiation – c and elevation – d) on the reforested area.

3.1. Relationships between structural complexity and topographic variables

Based on a 95% confidence interval, all the topographic variables had a significant effect on stand structural complexity (SSC). Results for the TWI classes One Way ANOVA were (F (2,85) = 22.563, p = 0.0005), with SSC difference between all TWI classes (Table 2). The slope classes had a significant difference on SSC (F(2,85) = 37.638, p = 0.0005), with only the fairly flat slopes having a different SSC from the intermediate and steep (Table 2). Area Solar Radiation (ASR) were (F(2,85) = 10.018, p = 0.0005), with only the fairly flat surfaces having a different SSC from the intermediate and high slopes (Table 2) while elevation were (F(2,84) = 6.294, p = 0.003) with only the low and high elevations with different SSC (Table 2). Stand age were (F (2,84) = 3.422, p = 0.037) – post-hoc test for elevation classes, with only the 2009/2010 and 2011/2012 sites having different SSC (Table 2). A summary of the mean stand structural complexities for the

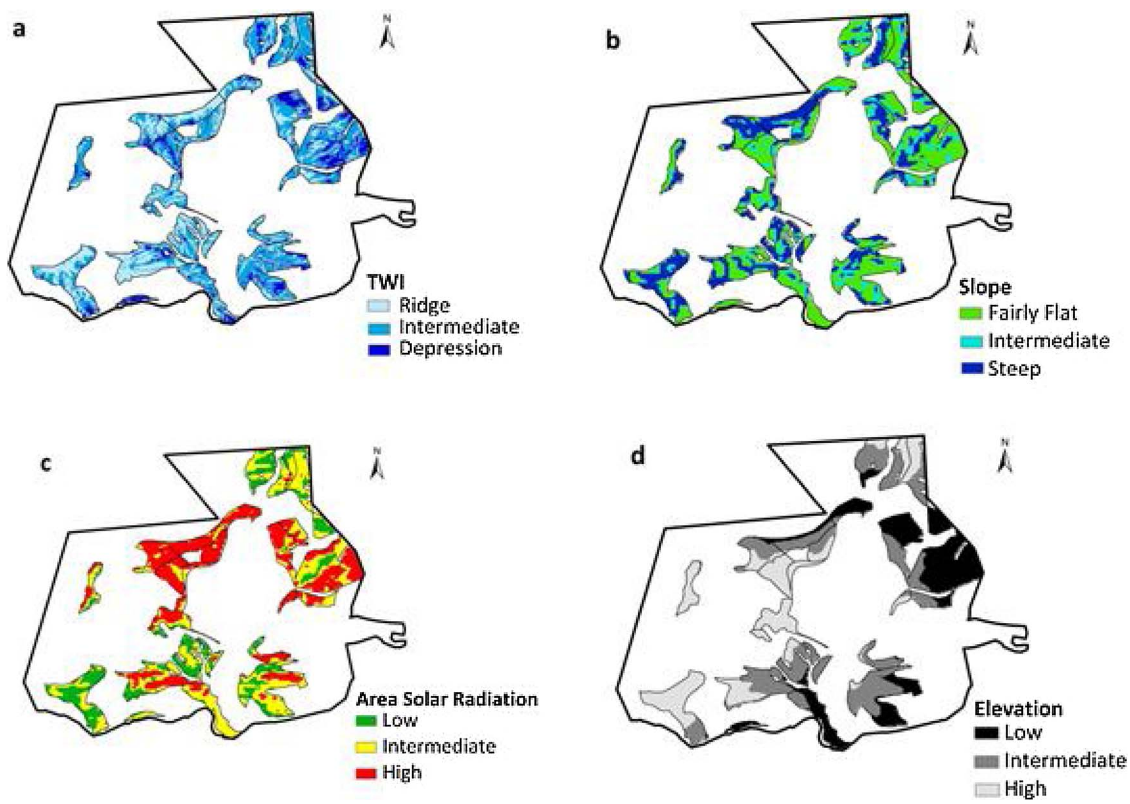

Fig. 4. The spatial distribution of the topographic variables extracted from the re-forested area (a – TWI, b – slope, c- Area Solar Radiation and d – Elevation. Kusasalethu Sithole; John Odindi; Onisimo Mutanga.

Table 2
Tukey's Post-Hoc Test of differences in SSC between classes.

Variable	Class	Class		
TWI		Ridges	Intermediate	Depressions
	Ridges	1		
	Intermediate	0.036	1	
	Depressions	0.0005	0.0005	1
Slope		Fairly Flat	Intermediate	Steep
	Fairly Flat	1		
	Intermediate	0.0005	1	
	Steep	0.0005	0.523	1
ASR		Low	Intermediate	High
	Low	1		
	Intermediate	0.04	1	
	High	0.0005	0.116	1
Elevation		Low Altitude	Intermediate	High Altitude
	Low Altitude	1		
	Intermediate	0.079	1	
	High Altitude	0.002	0.338	1
Stand Ages		2009/2010	2010/2011	2011/2012
	2009/2010	1		
	2010/2011	0.893	1	
	2011/2012	0.049	0.149	1

topographic classes and stand age is provided in Fig. 5. A correlation analysis showed that the TWI had the strongest correlation ($R = 0.72$), while stand age had the weakest correlation ($R = 0.27$) with SSC. Slope, ASR and elevation had a correlation of 0.69, 0.55 and 0.34, respectively.

3.2. Modelling stand structural complexity

To spatially model stand structural complexity (SSC) in relation topographic variables, PLS regression models were developed and their algebraic formulae derived (Eq. (3.10)). At an optimal latent variable number of 2, the PLS model for structural complexity index performed strongly at an RMSECV of 82.8637 and R^2 CV of 0.7485. Its NRMSECV was 0.129. Fig. 6 shows the spatial distribution of the structural complexity based on this PLS model. Based on the variable importance (VIP) function, TWI had the highest value of determining SSC (1.729), which was above slope (1.575), ASR (1.065), elevation (0.480) and stand age (0.350).

$$HC = 10.018*TWI-14.881*Slope + 0.0012*ASR-0.3016*Elevation + 14.370*Stand\ Age-13.441 \quad (3.10)$$

4. Discussion

The emergence of SSC as a superior indicator of ecological performance has increased the need for its spatially explicit information. This study sought to i) use topographic variables to predict SSC within a reforested urban landscape and ii) rank the importance of the topographic variables on these topographic patterns. To date, studies to determine SSC have been mainly adopted ecological data that include leaf area index, stem diameter, net primary productivity, basal area, tree height and species composition (Chave et al., 2005; Zheng et al., 2008; Aragão et al., 2009; Girardin et al., 2010; Ruiz-Labourdette et al., 2012; Valencia et al., 2004). Others have used remotely sensed image characteristics. Ozdemir and Karnieli (2011) for instance predicted SSC to a Gini coefficient 0.214814815 NRMSECV using the image texture derived from WorldView-2 imagery, while Jinghui et al. (2016) achieved a Pielou Index of 0.274 NRMSECV using the Spectral and Textural Information Derived from SPOT-5 Satellite Images. Using LIDAR composite metrics and machine learning, Zhao et al. (2011) predicted aboveground biomass and Leaf Area Index to 0.18 and 0.166 NRMSECV respectively while Castillo-Santiago et al. (2010) estimated basal area and canopy height to 0.228 and 0.161 NRMSECV respectively, using SPOT-5 satellite imagery. Using topographic variables and

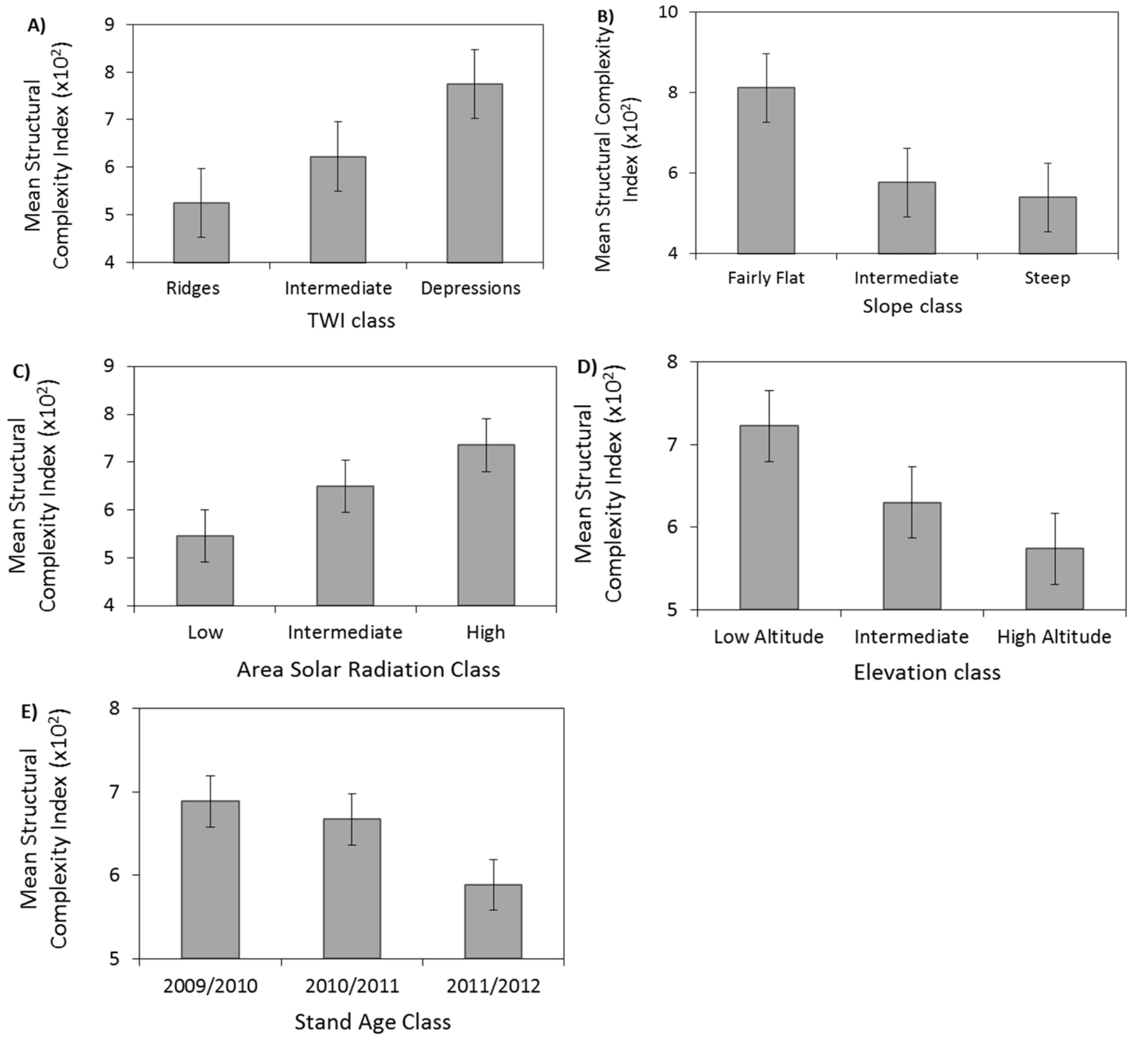

Fig. 5. Relationship between SSC and topographic variables a-TWI, b-Slope, c-Area Solar Radiation, d-elevation and d-Stand age (*Msc*I – Mean Structural Complexity Index). Kusasalethu Sithole; John Odindi; Onisimo Mutanga.

multispectral airborne imagery based on a redundancy analysis, Pasher and King (2010) captured only 35% of the total field variance, with an RMSE of 19.9%, while Cohen et al. (2001) attained a 12–23% RMSE prediction accuracy using forest cover attributes with the Landsat TM. Similar to Carrascal et al. (2009) and Luedeling and Gassner (2012), this study achieved a high prediction accuracy (0.129 NRMSECV). We attribute this higher prediction accuracy to the adoption of the PLS technique that reduced the complex and interrelated data into explanatory components of SSC, maximizing covariance with the topographic variables.

There was a visible spatial variation in SSC in different topographic variables, with TWI as a strongest predictor of SSC. TWI is determined by soil moisture's downslope gravitational movement, hence TWI typically increases downslope (Sörensen et al., 2006). As noted by Homeier et al. (2010) and Balvanera et al. (2002), this downslope soil moisture gradient increases downslope vegetation carrying capacity and SSC. According to Paoli and Curran (2007), the downslope soil moisture also creates nutrient pooling, hence trees in a depression or lower altitude benefit from relatively higher amounts of soil nutrients. In this study, the effect of the soil moisture gradient and associated nutrients is evident in the significant differences in SSC between all the slope ranges. Areas characterised by higher TWI (i.e. valley moisture sinks) had higher SSC than areas with lower TWI (i.e. ridge moisture drains).

In this study, slope was the second strongest predictor of SSC. The strong negative correlation between slope and SSC is consistent with Homeier et al. (2010) and Joseph et al. (2008). According to Webb et al. (1999), slope gradient represents the level of relative disturbance within a landscape. Steeper slopes are often more vulnerable to processes influenced by gravitation such as soil erosion and mass soil movement. Such processes results in erosion on steep slopes and deposition at gentle slopes and flatter areas, causing a topsoil and nutrient gradient, which influence SSC (Joseph et al., 2008, Takyu et al., 2002; Yirdaw et al., 2015).

Area Solar Radiation (ASR) had a moderate effect on the spatial distribution of SSC. ASR represents the variation in solar exposure as a result of the slope face direction. As aforementioned, its topographic variation creates a gradient in insolation, precipitation and transpiration (Kuebler et al., 2016; Wang et al., 2009; Webb et al., 1999), which may determine SSC. As insolation, precipitation and transpiration are known to strongly influence tree growth, ASR gradient creates a corresponding carrying capacity gradient, which influences SSC. In the southern hemisphere, north/east facing slopes are often characterised by higher SSC than the south/west facing slopes (Balvanera et al., 2002; Yirdaw et al., 2015). This is attributed to the southern hemisphere's often wetter and more humid north east – facing slopes and drier south west-facing slopes. However, due the moderate correlation between ASR and SSC in this study, it can be concluded that the limited variation in topography and insolation is a weaker determinant of SSC. Furthermore, the area experiences significant insolation throughout the

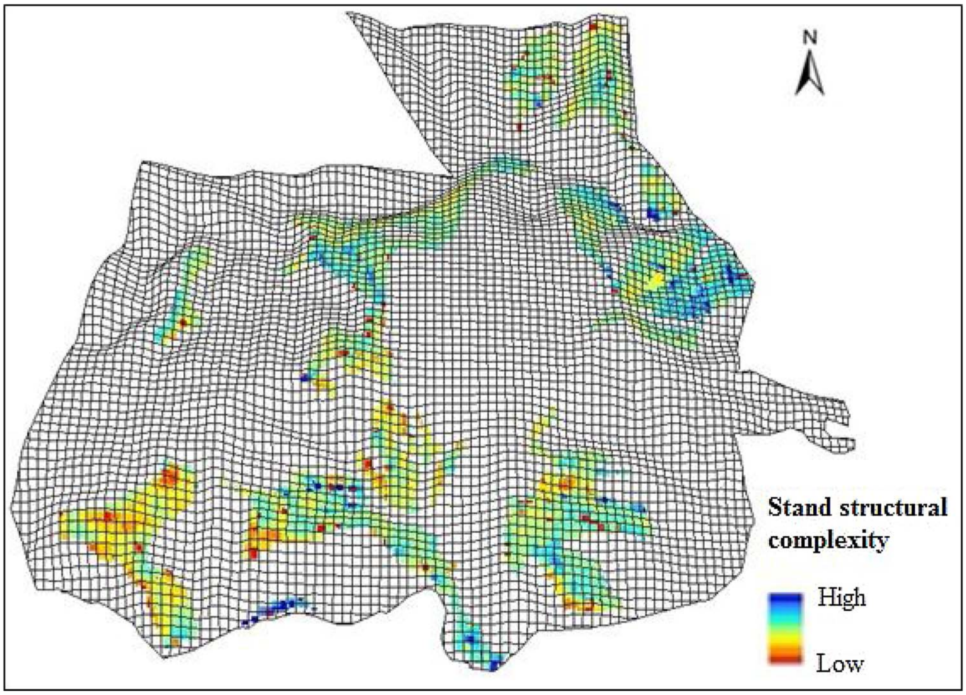

Fig. 6. The spatial distribution of predicted SSC.
Kusasalethu Sithole; John Odindi; Onisimo Mutanga.

year.

Although elevation was the least important topographic determinant of SSC, there was a significant difference in SSC between lower and higher altitudes. The downslope gravitational pull of loose soil acts as a practical proxy of edaphic gradients that directly affects tree growth (Clark and Clark, 2000; Oliveira-Filho et al., 2001; Wilcke et al., 2011). Other factors that may be influenced by altitude include soil fertility, soil moisture and soil and surface temperature (Fries et al., 2009; Ou et al., 2014; Wilcke et al., 2011; Wilcke et al., 2008; Wolf et al., 2011). Hence, Homeier et al. (2010) and Clark and Clark (2000) conclude that trees at the low elevations are often characterised by higher stand structural complexities. However, in contradiction to a number of studies (Clark and Clark, 2000; Homeier et al., 2010; Joseph et al., 2012), this study found a weak relationship between elevation and SSC. This can be attributed to the study area's "constrained geographic space" noted by Raes (2012) that leads to a weaker co-relation between elevation and vegetation growth.

Stand age is known to significantly influence tree size (Boninsegna et al., 1989; Burley et al., 2007), however in this study, stand age showed a weak positive correlation with SSC. Unlike single dimension tree attributes such as canopy height and stem diameter, SSC is influenced by other stand attributes like species richness, which do not necessarily increase linearly over time. For example, within the establishment and developmental years of reforestation, species richness change may be dramatically influenced by tree mortality (Lutz and Halpern, 2006; Van Mantgem et al., 2009) as well as other topographic variables, which could influence SSC.

As noted by Balvanera et al. (2002), an area's spatial extent strongly determines the influence of biophysical factors on SSC. At a localised landscape scale, the current study has shown that topographic variables like TWI and slope are strong determinants of SSC. In consistency with Gallardo-Cruz et al. (2009), this study established that different topographic variables, characterised by varying biophysical processes, have varying influences on the SSC. Hence, a combination of different topographic variables in this study was useful for predicting SSC in the reforested urban landscape. In this study the PLS technique and topographic datasets were useful in determining a reforested landscape's SSC. Such determination is valuable in the management of urban environment and mitigation of climate change, biodiversity loss and associated impacts.

5. Conclusions

This study set out to i) predict the spatial patterns in stand structural complexity (SSC) within a reforested urban landscape using topographic variables and ii) rank the importance of the topographic variables on these topographic patterns. The study findings show that;

- The PLS model performed with high accuracy in predicting SSC.
- The highest SSC was located at lower elevation in flatter depressions that were facing north/east.
- The importance of the variables in predicting SSC in decreasing order were TWI, slope, ASR, elevation and stand age.

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